Clustering in Urban environments: Virtual forces applied to vehicles

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***Abstract*—Clustering of Vanets is a technique for grouping nodes in geographical vicinity together, making the network more robust and scalable. Clustering of vehicles that is based on virtual forces has been recently introduced for highways. We propose a new algorithm, called Virtual Forces Vehicular Clustering ($VFVC$), to create stable clusters in Urban environments where mobility patterns of vehicles is more spatial. The algorithm uses combined metrics produced by vehicle's position, geometry, relative velocity and vehicle's lane in order to assign virtual forces among them and create clusters. The performance of the proposed algorithm is examined against two baseline algorithms and Spring clustering ($Sp - Cl$). Results obtained show that $VFVC$ performs better with a significant increase in cluster stability.**

I. Introduction

In cluster-based routing protocols vehicles near to each other form a cluster. Each cluster has one cluster-head, which is responsible for intra and inter-cluster management functions. Intracluster nodes communicate with each other using direct links, whereas inter-cluster communication is performed via clusterheaders. In cluster based routing protocols the formation of clusters and the selection of the cluster-head is an important issue. In VANET due to high mobility dynamic cluster formation is a towering process. Many clustering techniques for VANETS have been developed lately [1], [2], [3], [4], [5]. The cluster based methods are divided in five major categories. The methods that are focused in Urban environments, those that are suitable for a VANET environment on highways, methods that combine V2V and V2I communication and the two-tier architectures. One other category of clustering methods may be those that were initially produced for Manets can be used in Vanets with some modifications.

A well-known mobility-based clustering technique is $Mobic$ [6], which is an extension of the $Lowest - ID$ algorithm [7]. In $Lowest - ID$, each node is assigned a unique ID, and the node with the $Lowest - ID$ in its two-hop neighborhood is elected to be the cluster head. This scheme favors nodes with lower identifiers to become CHs without taking in mind mobility patterns of the nodes. In $Mobic$, an aggregate local mobility metric is the basis for cluster formation instead of node ID. The node with the smallest variance of relative mobility to its neighbors is elected as the cluster head.

Research supported by the project "REDUCTION: Reducing Environmental Footprint based on Multi-Modal Fleet management System for Eco-Routing and Driver Behaviour Adaptation", funded by the EU.ICT program, Challenge ICT-2011.7.

One of the major challenges in designing a vehicular network is the system scalability. The vehicular network should function in parameters for both low and high node density, regardless of the topology i.e. metropolitan, highway etc. Effective grouping of nodes in is achieved by applying clustering algorithms, built around the exchange of mobility context information between neighboring nodes. This information the most of the times is incorporated in the beacon messages.

In Urban environments where the mobility patterns of the vehicle is more chaotic the clustering techniques that are developed incorporate more complex metrics in order to create stable clusters [8], [9], [10]. Affinity propagation is an algorithm for image processing, and $APROVE$ has proved that its distributed case can be utilized for VANETs. $APROVE$ [8] distributively elects clusterheads by using affinity propagation from a communications perspective. Density-based clustering is based on a complex clustering metric which takes into account the density of the connection graph, the link quality and the road traffic conditions [9].

In [10] the proposed algorithm is based on the assumption that each vehicle knows its exact lane on the road via a lane detection system and an in-depth digital street map that includes lane information. The clusterhead is selected based on the flow of the majority of traffic. A lane weight (LW) metric is applied for each traffic flow (LT, RT and NT). The method does't take in mind future positions of vehicles in order to create clusters and only the current absolute difference of velocities is used in order to compute clusterhead level. Also vehicles lane changes are not simulated, but vehicles are assumed to follow a steady route. Lanes where are both turning and non-turning are also neglected. The method is used just before each intersection, since traffic is divided to flows according to the lane they belong to and checks whether the clusterhead stays the same just after the intersection and the results are not simulated on the total length of the road.

In [3] Spring clustering ($Sp - Cl$) was introduced, an algorithm performing cluster formation based on virtual forces applied to vehicles. The forces are computed taking into account accumulated metrics of the neighborhooding vehicles. Spring clustering shows increased performance for highways compared to $Lowest - ID$ [7] and LPG [7], however CH selection does not take into account critical vehicular parameters like the lane the vehicle belongs to, or social characteristics of the driver. These parameters are very important when Urban environments are investigated. In order to improve the grouping efficiency in such dynamic vehicular environments,

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characterized by frequent changes in direction, we propose a new clustering algorithm Virtual Forces Vehicular Clustering ($VFVC$). This algorithm is an extension of the Spring clustering algorithm proposed in [3], using a new complex optimized selection metric for the selection of cluster-head nodes based not only on current positions, future positions and relative velocities of vehicles but also on the lane they belong to.

The rest of the paper is organized as follows. In Section II, the network model is briefly described, in order to understand how vehicles are represented and how virtual forces are applied between the nodes. In section III the procedure which is used in order to assign electric load to vehicles according to special characteristics they have is described. The results of the simulations are presented in Section IV and finally, the conclusions are listed in Section V.

A. Contributions

The present work presents a new clustering protocol for VANETs. Several scenarios are investigated in a Urban environment where traces are loaded by SUMO [11] with several routing distributions.

The article makes the following contributions:

- A new distributed clustering method for Urban vehicular environments, the $VFVC$, is described.
- $VFVC$ incorporates current position of vehicles (Lane detection) in order to assign virtual forces on the vehicles.
- $VFVC$ exploits vehicle's height in order to choose the correct clusterhead.
- A performance evaluation of the proposed method against two baseline methods and Spring clustering is conducted, which attest the superiority of the new structure.

II. Virtual forces applied on Vehicles

Recently a clustering method with the use of virtual forces was introduced [3]. The method creates stable clusters in a highway. The basic idea lies in modeling vehicles as electrically charged particles. Every node applies to its neighbors a force F_{rel} according to their distance and their relative velocities. Vehicles that move to the same direction or towards each other apply positive forces while vehicles moving away apply negative forces. Components of the vector F_{rel} along the east-west F_x and north-south F_y axes are calculated.

In order to perform clustering nodes periodically broadcast beacon messages. Each beacon message consists of node Identifier (ID), node location, speed vector in terms of relative motion across the axes of x and y (dx, dy), total force F, state and time stamp. Each node i using the information of the beacon messages calculates the pairwise relative force F_{relij} for every neighbor applied to every axes j using the coulomb law.

$$F_{relijx} = k_{ijx}\frac{q_i q_j}{r_{ij}^2}, \quad F_{relijy} = k_{ijy}\frac{q_i q_j}{r_{ij}^2} \tag{1}$$

where r_{ij} is the current distance among the nodes, k_{ijx} (k_{ijy}) is a parameter indicating weather the force among the nodes is positive or negative depending on whether the vehicles are approaching or moving away along the corresponding axis and q_i and q_j may represent a special role of a node in terms of electric charge. The pairwise relative force $Frel_{ij}$ for every pair of nodes depends on the relative mobility $Krel_{ij}$, the current distance and parameters q_i and q_j which indicate a special role for the vehicles.

III. Vitrual Forces Vehicle Clustering

In our proposed scheme $VFVC$, we extend the meaning of special roles on vehicles used in $Sp-Cl$. The charge of every vehicle, is proportional to many parameters that affect its behavior in the network. All vehicles are assigned an initial electric charge Q. Vehicles according to their status (e.g. lane they belong to, car height, public transport etc.) are assigned a different amount of load ($Q(i)$) at each time step.

The characteristics that give vehicles extra charge are:

- Vehicles that follow predefined routes like a bus (Q_p)
- Tall vehicles like trucks (Q_T)
- Vehicles that follow non-turning lanes in a multi lane main street (Figure 1) ($Q_d(t)$).
- Vehicles that their driver behavior is statistically smooth (Q_b).
- Vehicles that based on historical data, mobility can be predicted (Q_h)

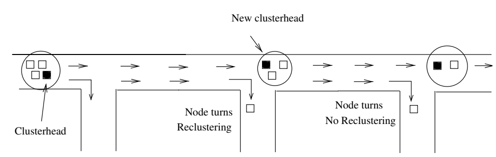

Fig. 1. The correct choice of the clusterhead plays significant role.

The total charge $Q(i)$ that is given to every vehicle at each time step according to the parameters described above, is given by equation 2. The only parameter that is dynamic is $Q_d(t)$ since the vehicle as it moves along the street may change lanes and follow turning or non turning lanes at different time steps.

$$Q_i = Q * Q_p * Q_T * Q_d(t) * Q_b * Q_h \tag{2}$$

In the simple scenario where all vehicles have the same characteristics and direction is not taken in mind all vehicles are equally charged

$$Q_i = Q \; \forall i, \; time\ step \tag{3}$$

and Virtual Forces Vehicular Clustering $VFVC$ performs like the original $Sp-Cl$.

Using equation 4 to compute the relative force between two nodes, parameter q_i is used as follows:

$$\text{if } k_{ijx} \geq 0 \text{ then } q_i = 2 * Q(i), \text{if } k_{ijx} \leq 0 \;\text{ then } q_i = Q(i)/2. \tag{4}$$

In order to enhance the performance of the method in Urban environments we incorporate in every beacon message one additional byte of information about the lane the vehicle belongs to. Positive forces applied to these nodes are strengthened while negative are weakened, in order to facilitate this node to become a clusterhead. The correct choice of the clusterhead is very important for the stability of the method, the cluster lifetime and the overhead involved in forming and maintaining these clusters.

A. Direction matters, parameter $Q_d(t)$

In urban environments where vehicles change directions often, parameters concerning direction need to be taken in mind in order to perform clustering. The $VFVC$ method that we propose uses parameter $Q_d(t)$ in order to favor vehicles to become clusterheads according to the lane they belong to. There are three main traffic flows at an intersection: Left Turn (LT), Right Turn (RT), and No Turn (NT). The intersection may have all three types of traffic flows or only some of them. LT is applied to the leftmost lane(s) if it splits the traffic to the left, RT is applied to the rightmost lane(s) if it splits the traffic to right, while NT is applied to the lane(s) in the middle if traffic goes straight.

In a multi-lane street vehicles that follow a non turning lane are better candidates to become clustrheads since they are going to stay longer on the street. If a vehicle that is going to leave the street soon, is elected as a clusterhead then major re-clustering is going to take place when it turns to another road segment, since it leaves all of its members orphans. In case a member node i leaves the street in order to follow another edge of the network, only this vehicle tries to find a nearby cluster to enter. Charges are assigned to cars according to the lane they belong according to the following rules.

- If the car follows a non turning lane then $Q_d(t)$=2
- If the car follows a turning lane then $Q_d(t)$=1
- If lane the car belongs to is going straight or turns then the $Q_d(t)$=1.5

In most of the cases this method increases the performance of spring clustering since expect from the most stable node in terms of relative mobility and velocity also a sense of future direction is used in order to perform clustering.

B. Lane Detection

Virtual Forces Vehicular clustering is based on the assumption that each vehicle knows its exact lane on the road via a lane detection system and a digital street map [12]that includes lane information for every road segment. Localization of vehicles in mainly conducted through GPS either as a standalone system or combined with a wheel odometer [13] for better detection of lane changes.

Also a beacon network using infrastructure to triangulate vehicle position can be used [14]. Other algorithms do not use GPS, and instead use techniques such as vision [15], LIDAR (Light Detection and Ranging) [16] etc. In case a vehicle isn't equipped with any localization mechanism, relative positions of its one hop neighbors could be used in order to detect its lane with a good precision.

IV. Simulation and Performance Evaluation

Our proposed clusterhead selection algorithm was evaluated through detailed simulation on an urban environment. We simulated an area from city of Volos in Greece that is shown in figure 2 and is 2km x 600m.

Fig. 2. Urban area of Volos

After aggregating the road segments that have the same attitudes we have simulated the area in SUMO as shown in figure 3

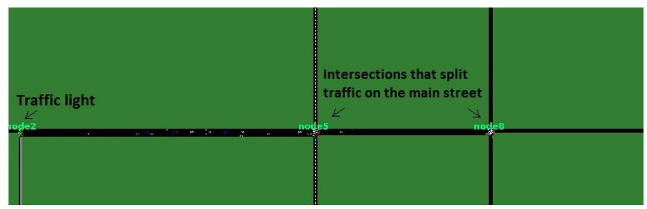

Fig. 3. Simulated Urban area of Volos

The area consists of thirteen intersections. Only intersections 5 and 8 (see figure 3) split the traffic of the main street of interest. The intersections split the traffic into three different directions. The first intersection has four lanes, dividing the traffic into two directions: one lane to the right (TR) and three lanes going straight (NT). The second intersection has three lanes, dividing the traffic into two directions: one lane to the left (TL) and two lanes going straight. We focused only on one traffic direction.

Vehicles follow three different route distribution according to table I. These distributions are used in order to favor vehicles follow the main street or turn in the intersections in a probabilistic way and not follow deterministic routes. The

Route	*Intersection 5*		*Intersection 8*	
	NT	*TR*	*NT*	*TL*
1	80%	20 %	90%	10%
2	80%	20 %	10%	90%
3	20%	80 %	50%	50%

TABLE I
Route distributions

vehicle type ratio used for this simulation was 15% trucks and 85% sedans. We inject vehicles on the road and for the first 110 seconds of simulation time we use a traffic light in the beginning of the area of interest. A traffic light is used in order to have all vehicles injected as a group in the area. We follow them until they leave the straight section of the road turning left or right. In that way we are focusing on what happens on a central road, where cars enter and leave it all the time, if we favor cars that follow the non turning lane to become clusterhead. The parameters of $VFVC$ used in the simulation scenarios are listed in table II.

$VFVC$ parameter	Simulated	Parameter value
$Predefined\ routes$	No	1 (default)
$Vehicle's\ Height$	Yes	2(Tall), 1(Short)
$Vehicle's\ Lane$	Yes	2(NTL), 1.5 (TL & NTL), 1(TL)
$Driver\ behavior$	No	1 (default)
$Mobility\ prediction$	No	1 (default)

TABLE II
PARAMETERS OF VIRTUAL FORCES VEHICULAR CLUSTERING.

The traffic simulation is conducted with SUMO [11] and the trace files are injected to our custom simulator in order to perform clustering. We ran 10 different runs for each scenario of different communication ranges and speed limits. The vehicles were given different maximum speeds to provide a realistic highway scenario. Random maximum speeds were assigned to the different vehicles by providing SUMO with a probability distribution input.

Scenario	Transmission Range	Max Speed limit
1	130 m	80 - 36 Km/h
2	200 m	80 - 36 Km/h
3	250 m	80 - 36 Km/h
4	300 m	80 - 36 Km/h

TABLE III
SCENARIOS TESTED DURING THE SIMULATION.

All nodes are equipped with GPS receivers and On Board Units (OBU). Location information of all vehicles/nodes, needed for the clustering algorithm is collected with the help of GPS receivers. The only communications paths available are via the ad-hoc network and there is no other communication infrastructure. The power of the antenna is P_{tx} = 18dBm and the communication frequency f is 5.9 Ghz.

The reliable communication range of the vehicles is calculated according to Table IV. The reliable communication range is calculated for every pair of nodes at every instance based on the diffraction caused by obstructing vehicles [17]. In our simulations, we use a minimum sensitivity (P_{th}) of -69 dBm to -85 db which gives a transmission range of 130 to 300 meters.

Data Rate (Mb/sec)	Minimum Sensitivity(dBm)
3	-85
4.5	-84
6	-82
9	-80
12	-77
18	-70
24	-69
27	-67

TABLE IV
MINIMUM SENSITIVITY IN RECEIVER ANTENNA ACCORDING TO DATA RATE.

In order to evaluate the stability of the algorithm, we measure the stability of the cluster configuration against vehicle's mobility. In a high dynamic VANET, nodes keep joining and leaving clusters along their travel route. Good clustering algorithms should be designed to minimize the number of cluster changes of the vehicle by minimizing reclustering. This transitions among clusters are measured in order to evaluate the performance of the algorithm.

The basic transition events the vehicle encounters during its lifetime:

- A vehicle leaves its cluster and forms a new one (becomes a clusterhead).
- A vehicle leaves its cluster and joins a nearby cluster or becomes free.
- A cluster-head merges with a nearby cluster.

We compare the average transition events of the vehicles for the Virtual Forces Vehicular clustering ($DFVC$), $Sp-Cl$ [3],$Lowest-ID$ [7] and $Mobic$ [6] methods when different transmission ranges are used. From Figure 4, we can see the average cluster lifetime is bigger compared to that produced by the $Sp-Cl$, $Lowest-ID$ and $Mobic$ methods. The average clusterhead duration is the average length of time that a node remains a clusterhead, once it has been elected. Long clusterhead duration is important for MAC schemes where the clusterhead is the central controller and scheduler. Frequent changes to the clusterhead will degrade the performance of these cluster-based MAC schemes.

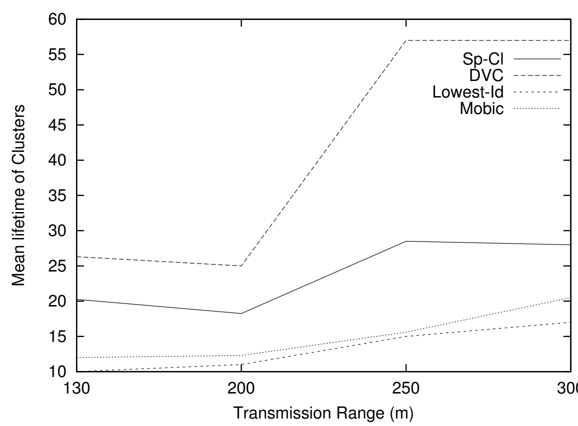

Fig. 4. Average cluster lifetime vs transmission range

In this simulation we counted the new clusters which are added to the system. To effectively decrease network contention, fewer clusters is desirable. Typically, clustering algorithms strive to have only one clusterhead within a given broadcast range. Figure 5 shows that the total number of clusters created by $VFVC$ is always smaller compared to that produced by the other methods and this number decreases as the transmission range increases. The number of clusters is decreased compared to $Sp-Cl$ due to the fact that except current and future position and relative velocities among vehicles, also direction expressed in terms of the street lane occupied by the vehicle is used in order to select the more stable clusterhead.

From Figure 6, we can see that the average transitions produced by our $VFVC$ technique is very small compared to the other methods. The average rate of clusterhead change is the overall average number of clusterhead changes per second.

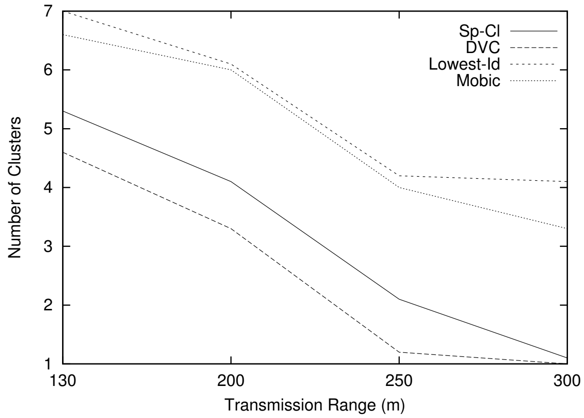

Fig. 5. Average number of clusters for different transmission ranges.

The more clusters that are present, the greater the number of clusterhead changes; therefore this metric conveniently considers both clusterhead duration and the number of clusters formed. Similar figures were produced for different speed limits.

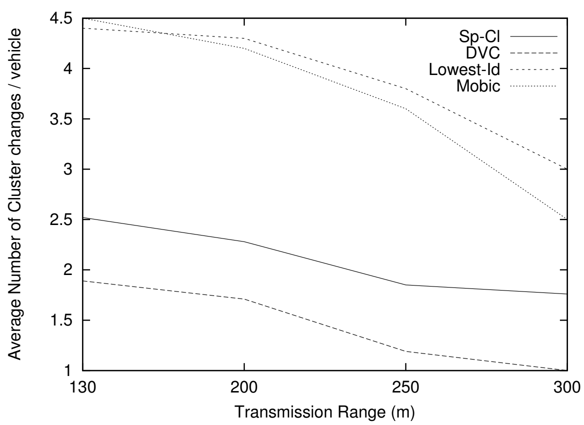

Fig. 6. Clusterhead changes vs transmission range

The results clearly indicate that favoring vehicles that follow non turning lanes has a significant impact on the formation of clusters in a typical VANET clustering urban scenario where a major city area is simulated.

V. CONCLUSIONS - FUTURE WORK

Clustering can provide large-scale Vanets with a hierarchical network structure to facilitate routing operations. Virtual forces which are applied to vehicles from their one hop neighbors reflect the ratio of divergence or convergence among them. We proposed a clustering solution with combined metrics such as vehicle geometry, current and future distance among the vehicle, relative velocities and current lane of vehicles in order to make clustering more stable in urban environments.

The results of simulations conducted show that $VFVC$ algorithm outperforms the other investigated methods, in terms rate of cluster-head changes (lower), total number of clusters (lower), average cluster lifetime(higher), translated in increased cluster stability, lower percentage of orphan nodes and larger cluster sizes. The stable clusters created by $VFVC$ can be used as a base so typical VANET routing algorithms can be applied for intra-cluster routing.

More sophisticated approaches where the future direction of the vehicles according to the drivers behavior are needed in order to further cope with temporal mobility patterns that appear in urban environments. A research on clustering solution that exploits sociological patterns of vehicular movement is conducted by our group, based on our previous work [18]

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